A speech model of acoustic inventories based on asynchronous interpolation

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Abstract
We propose a speech model that describes acoustic inventories of concatenative synthesizers. The model has the following characteristics: (i) very compact representations and thus high compression ratios are possible, (ii) re-synthesised speech is free of concatenation errors, (iii) the degree of articulation can be controlled explicitly, and (iv) voice transformation is feasible with relatively few additional recordings of a target speaker. The model represents a speech unit as a synthesis of several types of features, each of which has been computed using non-linear, asynchronous interpolation of neighboring basis vectors associated with known phonemic identities. During analysis, basis vectors and transition weights are estimated under a strict diphone assumption using a dynamic time warping approach. During synthesis, the estimated transition weight values are modified to produce changes in duration and articulation effort.

1. Introduction
The capabilities of mobile electronic devices are continuously expanding due to improvements in hardware design and manufacturing. For example, today’s cell phones can run complex office productivity software, audio and video players, and Internet browsers. Obviously, speech technologies are highly desirable in mobile units, which typically feature limited input and output interfaces, and are often used in hands-off, eyes-off tasks. One of these technologies is a text-to-speech (TTS) system which allows the user to receive information by listening.

There are two viable TTS technologies today: formant synthesis and concatenative synthesis. In formant synthesis, great flexibility is achieved by controlling important speech features explicitly; however, the resulting speech, while highly intelligible, often sounds unnatural. A concatenative synthesizer, on the other hand, takes pre-recorded speech units from its acoustic inventory (AI), optionally modifies them prosodically, and joins them together to produce a more natural-sounding speech utterance. However, audible discontinuities at concatenation points or excessive signal processing, due to a mismatch in phonetic or prosodic context, may degrade the speech quality. To feature a variety of phonetic contexts and thus reduce the number of concatenations, an acoustic inventory typically holds many thousands of units, whose lengths may vary from short phoneme pair units (diphones) to words and phrases.

With the price of storage continually decreasing, concatenative systems with large AIs have become feasible on personal computers and servers. However, the implementation of such a system on embedded hardware is proving difficult because of the large memory requirements ranging from tens to thousands of megabytes. Since the perceived quality of a concatenative TTS system is directly related to the number and length of available units, a compression technology for AIs is extremely useful for any storage-limited device.

Although the area of speech coding has produced many compression algorithms, none of them are specifically designed to compress an AI, which differs from general speech coding in several respects:

• An AI contains speech from a single speaker in acoustically constant and noise-free conditions. General purpose speech coders, however, are designed to work with a variety of speakers and environments.
• An algorithm designed expressly for the compression of an AI can be highly complex computationally because processing is performed offline, as long as decoding is sufficiently fast. Furthermore, the algorithm can greatly capitalize on the availability of the complete dataset. In contrast, typical speech coders must provide very low latency and are thus limited to real-time solutions working on very short signals at a time.
• An AI contains information about the stored speech signals. At a minimum, the speech is segmented and labeled phonetically, but the inventory may also contain prosodic features and pitch marks. Also, a high quality AI has the close acoustic match property, which means that the units are recorded to be maximally compatible in the sense that their concatenation with each other reduces audible spectral discontinuities as much as possible. This additional structure and information is extremely advantageous for compression.

In this paper, we propose a model that describes the speech in an AI. Compression or coding is equivalent to fitting the parameters of the model, whereas decompression or decoding is equivalent to synthesizing speech from the stored parameters. In addition, our speech model forms a conceptual bridge between concatenative and formant synthesizers, merging the natural speech quality of concatenative synthesis with the flexibility of formant synthesis. It has the following characteristics:

• By taking advantage of the special properties of an AI, the minimally required model parameter set makes very high compression ratios possible. However, it is also possible to specify a quality or size criterion for variable compression rates.
• The synthesized speech is free of any concatenation artifacts because the regions of speech that are near potential concatenation points are represented as a single set of parameters, thus exploiting the close acoustic match property.

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An explicit coarticulation model allows for control over the articulation effort or degree of articulation, which is especially important when changing the speaking rate. When the number of the model parameters is sufficiently small, information about the segmental characteristics of the original speaker can be easily replaced with that of another speaker, allowing for a transformation of the synthesis voice to sound like any desired target speaker without recording a full AI.

2. Method

2.1. Core Idea

The core idea of our speech model is to represent a speech unit as a synthesis of several types of features, each of which has been computed using non-linear, asynchronous interpolation of neighboring basis vectors. Each basis vector can be associated (labeled) with a particular phoneme, allophone, or smaller unit. Labels may contain additional information about context and prosody.

In its most general form, we approximate the complex speech spectrum $X$ at frame $m$ of the $i$th unit by letting

$$\hat{X}^{UIr}(m) = T(p_1, p_2, \ldots, p_N)$$

where $U = u_1, \ldots, u_{i-1}, u_{i+1}, \ldots, u_{i+r}$ represents the context of $l$ left neighbors and $r$ right neighbors. (We drop most indices in the interest of readability.) $T$ is a synthesis function that is given $N$ interpolated speech feature vectors $p$, which are calculated using

$$p_m = \sum_{i=1}^{r} w_{mir}(m) \cdot M_{i\rightarrow} (b_{m}^{u})$$

where $w$ are the non-negative transition weights for basis vectors $b$ modified by a modification function $M$. For each unique label in the AI there exist $N$ types of basis vectors, which are feature vectors describing various aspects of the underlying speech signal. The transition weights, which are subject to the condition

$$\sum_{i=1}^{r} w_{mir}(m) = 1 \ \forall n, m$$

determine the relative contribution of each of the $l+r+1$ modified basis vectors for a particular $n$ and $m$. The purpose of $M$ is to introduce additional flexibility into the model, for example allowing an already calculated $p_m$ to influence the calculation of $p_{n+1}$.

The idea of modeling speech by interpolating basis vectors is not new, as exemplified by Atal’s Temporal Decomposition method [1]. However, our proposed method is fundamentally different in that the phonemic identities of the basis vectors are known, and several asynchronous, non-linear interpolations are involved.

2.2. Implementation

In our current work, we experiment on the diphone database “MWM” from the OGIresLPC package [2]. We select a slightly revised set of American English phonemes as labels. Since some phonemes describe more than a single acoustic event, we represent them by two or more transitions involving several basis vectors: we (i) split diphthongs into two parts, e.g. /ai/ = /aI/ → /aI/ + /ai/2/, where the diacritic distinguishes between the two different acoustic targets, (ii) split unvoiced plosives into three parts: the closure, burst, and aspiration, e.g. /l/ = /h/ → /hl/ → /hl/ , and (iii) represent affricates and syllabics as a combination of other basis vectors, e.g. /AS/ = /h/ → /S/ and /aI/ = /&/ → /l/.

We select three types of basis vectors: a list of formant-like frequencies describing spectral “landmarks” ($b_{form}$), and short-term magnitude ($b_{spect}$) and phase ($b_{phase}$) spectral information. In our implementation, Eq. (1) reduces to

$$\hat{X}^{UIr}(m) = T(p_{spect}, p_{phase})$$

where the synthesis function $T$ is equivalent to the construction of a complex spectrum from magnitude and phase spectra. The interpolated speech features are defined as

$$p_{spect} = \sum_{i=1}^{r} w_{spect}(m) \cdot M (b_{form}, b_{spect}, p_{form})$$

$$p_{phase} = \sum_{i=1}^{r} w_{phase}(m) \cdot M (b_{form}, b_{phase}, p_{form})$$

$$p_{form} = \sum_{i=1}^{r} w_{form}(m) \cdot b_{form}$$

where $M$ is a function that warps magnitude and phase spectra along the frequency axis. Specifically, given a particular spectrum and its landmarks, $M$ calculates a non-uniform resampling of the original frequency locations and returns a magnitude spectrum with landmarks at $p_{form}$ (see Fig. 1). Note that even though there are 3 types of basis vectors, the transition weights for the spectral parameters are tied.

Eq. (5) is based on the observation that in transitions between most phonemes, formants and the overall spectral shape change asynchronously. For example, a transition from /i/ to /l/, as in the word “leave”, shows a change in formants that starts well before the onset of frication. Another motivation is to model the speech spectrogram as a “morphing” between different speech sounds. Similar to the process of image morphing,
we use formants as salient features to render a good approximation of the transition between two sounds, one which could not be achieved by simply cross-fading. Yet another way to view the system is as a formant synthesizer whose formant trajectories are fitted to the speech in the AI, but one that merges additional information about the overall spectral shape, resulting in more natural synthesis.

3. Analysis

3.1. Estimating basis vectors

For each label, we select a representative location in the AI manually (for an automatic approach see [3]). To estimate spectral basis vectors \( b_{\text{spec}} \) and \( b_{\text{form}} \), a pitch-synchronous sinusoidal analysis is carried out. To estimate \( b_{\text{form}} \), we manually determine formant frequencies \( f \) and bandwidths \( b \) and construct a sorted list of frequencies of the form \( \{f_1 - b_1, f_1 + b_1, f_2 - b_2, f_2 + b_2, \ldots, f_k - b_k, f_k + b_k, C\} \), where \( C \) is a constant upper limit frequency beyond which no spectral modification is desired. When formants were not visible, formant frequencies from locus theory were used [4].

3.2. Estimating transition weights

During analysis, we assume the close acoustic match property to hold perfectly, i.e. the boundaries of diphone units are assumed to be free of coarticulation. For analysis purposes, we estimate transition weights during compression or expansion of a transition. While various strategies have been suggested [5], we prefer to hold perfectly, i.e. the boundaries of diphone units are as defined to be free of coarticulation. For analysis purposes, we assume the close acoustic match property to hold perfectly, i.e. the boundaries of diphone units are assumed to be free of coarticulation. For analysis purposes, we estimate transition weights during compression or expansion of a transition. Often it is desirable to customize a TTS system with a new voice, but only few recordings of the new speaker are available or practical. A possible strategy for this in the context of the proposed implementation is to simply replace the basis vector information (complex spectrum and formant frequencies and bandwidths), but leave the transition weights unchanged. This approach is effective in changing the synthesized voice to the degree that transition weights are speaker-independent.

An example application of voice transformation exists in the context of assistive technologies for people who present with a motor speech impairment or dysarthria. The ability to

4. Synthesis

Phoneme durations, and thus distances between basis vectors, are generally different from those seen during the analysis step. Therefore, a strategy must be devised for arranging the transition weight values during compression or expansion of a transition. While various strategies have been suggested [5], we propose to preserve the articulation effort during changes to

duration. Specifically, transition weights can be expanded by stretching only the center of the transition trajectory (see Fig. 3). However, they cannot be compressed any further: if a desired transition is shorter than what is stored, the influence of the current phoneme will reach beyond the current diphone context. In order to control the articulation effort and make fast speech possible, we introduce a parameter \( \alpha \) that scales the timing of a transition around unit boundaries. The behavior is as follows: for \( \alpha = 1 \), nothing is changed; if the distance between two basis vectors is halved, then a setting of \( \alpha = 2 \) will increase the articulation effort such that the transitions will complete in the context of the diphone (as originally during analysis). In this manner it is possible to control the degree of articulation at any speaking rate, rendering speech as more hypo-articulate or hyper-articulate. In contrast, changes to duration using common techniques such as PSOLA are coupled with uncontrolled changes to articulation effort [6].

Finally, Eq. (4) and (5) are used to calculate the complex spectrogram of the new sentence. The final time domain signal is calculated by a pitch-synchronous sinusoidal synthesis method (see Fig. 4).

5. Voice Transformation

Often it is desirable to customize a TTS system with a new voice, but only few recordings of the new speaker are available or practical. A possible strategy for this in the context of the proposed implementation is to simply replace the basis vector information (complex spectrum and formant frequencies and bandwidths), but leave the transition weights unchanged. This approach is effective in changing the synthesized voice to the degree that transition weights are speaker-independent.

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Therefore, a search algorithm is needed that derives the optimal labeling set. This approach promises to be highly suitable for the compression of large unit-selection databases, where many concatenation points exist and a manual selection of labels is suboptimal and impractical.

**Estimating transition functions.** Typically, transition weight functions display a certain regularity which can be exploited by approximating them by a parameterized function, such as a sigmoid. Such a scheme would allow a decrease in the number of model parameters, resulting in a higher compression ratio.

**Parameter Sharing.** It can be observed that weight trajectories for certain types of transitions, such as vowel to nasal transitions, are similar. Therefore, transition weight trajectories may be shared between all transitions of this type, resulting in a further decrease in the number of model parameters.

## 7. References


